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An improved support vector regression and its modelling of manoeuvring performance in multidisciplinary ship design optimization

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ABSTRACT

In this paper, the combination of the Laplace loss function and support vector regression (SVR) is presented for the estimation of manoeuvring performance in multidisciplinary ship design optimization, and a new SVR algorithm was proposed, which has only one parameter to control the errors and automatically minimized with ν , and adds $b^2/2$ to the item of confidence interval. It is shown that the proposed SVR algorithm in conjunction with the Laplace loss function can estimate the ship manoeuvring performance appropriately compared to the simulation results with Napa software and other approximation methods such as artificial neural network and classic SVR. In this article, we also gather enough ship information about the offshore support vessel; the Latin Hypercube Design is employed to explore the design space. Instead of requiring the evaluation of expensive simulation codes, we establish the metamodels of ship manoeuvring performance; all the numerical results show the effectiveness and practicability of the new approximation algorithms.

ARTICLE HISTORY

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KEYWORDS

Metamodel; support vector machine; multidisciplinary design optimization; ship manoeuvring

1. Introduction

In the ship design process, there is often more than one element; that is, there may be different disciplines which contribute to the ship design, [1] such as structures, economics or hydrodynamics. The disciplines may be studied with different software tools, or investigated by different teams of engineers. Due to these complexities, the ship design problem cannot be formulated simply as a single optimization statement. Therefore, it is necessary to improve the algorithm of multidisciplinary design optimization (MDO) and its goal is to develop the methodology to coordinate different discipline optimizations, and achieve a design plan that optimizes all disciplines. [2–4]

The development of ship design technology is dependent upon a cooperative, multidisciplinary design approach. To reduce the computational cost of computer-based simulations and analyses in ship design, a variety of metamodeling techniques have been developed, [5–7] for instance, response surface model, kriging and artificial neural network (ANN). Metamodel is a key element of the MDO [8–10]. In this paper, a new simple and effective algorithm of support vector machines is proposed and used to establish the metamodels of ship manoeuvring performance in the multidisciplinary ship design optimization.

2. Improved mathematical model of ν -SPL-SVR

It is important to improve the accuracy and robustness performance of metamodeling techniques, especially when the sample

size becomes small and limited. The SVR algorithm aims at limited samples and has a good generalization performance as well as global optimal extremum which have been proved by many scholars. [11] Inspired by the reference [13], a modification of single-parameter Lagrangian support vector regression (SPL-SVR) [12] was proposed in this paper, called ν -SPL-SVR. Given a set of data points, $\{(x_1, y_1), (x_2, y_2), \dots, (x_l, y_l)\}$, such that $x_i \in R^n$ is an input and $y_i \in R^1$ is a target output, the primal problem is list as follows:

$$\begin{cases} \text{Min} \frac{1}{2} w^T w + \frac{1}{2} b^2 + C \left(\nu \varepsilon + \sum_{i=1}^l |\xi_i| \right) \\ \text{such that } |y_i - w^T \phi(x_i) - b| \leq \varepsilon + \xi_i \\ \varepsilon \geq 0, \xi_i \geq 0, 0 \leq \nu \leq 1, i = 1, \dots, l \end{cases} \quad (1)$$

Here, $\frac{1}{2} w^T w$ is a term which characterizes the model complexity. C is the penalty parameter, and training vectors x_i are mapped into a higher (maybe infinite) dimensional space by the function ϕ . The ε -insensitive loss function means that if $w^T \phi(x_i)$ is in the range of $y \pm \varepsilon$, no loss is considered. The formulations use parameters C and ε to apply a penalty to the optimization for points which were not correctly predicted.

As it is difficult to select an appropriate ε for SPL-SVR, so here we introduce a new parameter ν , which is an upper bound on the

fraction of margin errors and a lower bound of the fraction of support vectors. Also the parameter ν lets one control the number of support vectors and training errors. For the constraints, we introduce multipliers α_p , α_i^* , η_p , β and obtain the Lagrange function:

$$L = \frac{1}{2}(w^T w + b^2) + C\nu\varepsilon + C \sum_{i=1}^l |\xi_i| - \sum_{i=1}^l \alpha_i [\varepsilon + \xi_i - y_i + w^T \phi(x_i) + b] - \sum_{i=1}^l \alpha_i^* [\varepsilon + \xi_i + y_i - w^T \phi(x_i) - b] - \sum_{i=1}^l \eta_i \cdot \xi_i - \beta \varepsilon \quad (2)$$

It follows from the saddle point condition that the partial derivatives of L with respect to the primal variables (w , b , ξ_i , ε) have to vanish for optimality.

$$\frac{\partial L}{\partial b} = b - \sum_{i=1}^l (\alpha_i - \alpha_i^*) = 0 \quad (3)$$

$$\frac{\partial L}{\partial w} = w - \sum_{i=1}^l (\alpha_i - \alpha_i^*) \cdot \phi(x_i) = 0 \quad (4)$$

$$\frac{\partial L}{\partial \xi_i} = C - \alpha_i - \alpha_i^* - \eta_i = 0 \quad (5)$$

$$\frac{\partial L}{\partial \varepsilon} = C\nu - \beta - \sum_{i=1}^l (\alpha_i + \alpha_i^*) = 0 \quad (6)$$

A kernel function $K(x_i, x_j) = (\phi(x_i) \cdot \phi(x_j))$ is introduced into the formula, which can map the non-linear high-dimensional design space into linear low-dimensional design space with a radial basis function (RBF) [14] is $K(x_i \cdot x_j) = \exp(-\beta \|x_i - x_j\|_2)$. The dual optimization problem is shown as follows:

$$\begin{aligned} & \text{Min} \frac{1}{2} \sum_{i,j=1}^l (\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*) [K(x_i \cdot x_j) + 1] - \sum_{i=1}^l (\alpha_i - \alpha_i^*) \cdot y_i \\ & \text{such that } (\alpha_i + \alpha_i^*) \leq C, \sum_{i=1}^l (\alpha_i + \alpha_i^*) \leq C\nu \\ & \alpha_i, \alpha_i^* \geq 0 \end{aligned} \quad (7)$$

Compared to the SPL-SVR, there is no ε in the objective function (7), which means we do not have to decide on the ε for insensitive loss function before optimization. The above optimization problem can be stated as in a standard formulized quadratic programming.

$$\begin{aligned} & \text{Min} \frac{1}{2} X^T H X + d^T X \\ & \text{such that } A X \leq C^*, B X \leq C^* \nu, X \geq 0 \end{aligned}$$

$$\begin{aligned} & \text{where } X = \begin{bmatrix} \alpha \\ \alpha^* \end{bmatrix}_{2l \times 1}, H = \begin{bmatrix} K & -K \\ -K & K \end{bmatrix}, \\ & \alpha^{(*)} = [\alpha_1^{(*)}, \alpha_2^{(*)}, \dots, \alpha_l^{(*)}]^T, C^* = [C, C, \dots, C]_{1 \times 2l}^T, \\ & Y = [y_1, y_2, \dots, y_l]^T, B = [1, 1, \dots, 1]_{1 \times 2l}, d = \begin{bmatrix} -Y \\ +Y \end{bmatrix}_{2l \times 1}, \end{aligned}$$

Thus, the estimation function is calculated as follows:

$$f(x) = \sum_{i=1}^l (\alpha_i - \alpha_i^*) (K(x_i \cdot x) + 1) \quad (8)$$

$$A = \begin{bmatrix} 1 & 0 & \dots & 0 & 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 & 0 & 1 & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & 1 & 0 & 0 & \dots & 1 \end{bmatrix}_{l \times 2l},$$

$$K = \begin{bmatrix} K(x_1, x_1) + 1 & K(x_1, x_2) + 1 & \dots & K(x_1, x_l) + 1 \\ K(x_2, x_1) + 1 & K(x_2, x_2) + 1 & \dots & K(x_2, x_l) + 1 \\ \dots & \dots & \dots & \dots \\ K(x_l, x_1) + 1 & K(x_l, x_2) + 1 & \dots & K(x_l, x_l) + 1 \end{bmatrix}_{l \times l}$$

With this simpler algorithm, we can obtain the black box which describes the complicated mapping relation without knowing the connection between the dependent variables and independent variables. Therefore, this new algorithm is suitable for the construction of a ship manoeuvring approximation model in the MDO for the ship preliminary and early-stage design.

3. Distribution of ship samples

Before constructing the metamodels of ship manoeuvring performance, we need to gather plenty of ship information and select the training ship data-set. Here, we choose Latin Hypercube Designs as the method of design of experiments. The Latin Hypercube method chooses points to maximize distance between design points with a constraint which maintains the even spacing between factor levels. At the same time, plenty of data measuring offshore support vessels were gathered from many shipping companies and design institutions. The distributions of the main principal characteristics are shown in Figure 1, in which the red points represent the 20 training ship data

4. Establishment of metamodels of ship manoeuvring performance

As is well known, there are many variables which affect ship manoeuvring performance. Here, we chose the length between perpendiculars, breadth, depth, design draught, longitudinal centre of buoyancy, ship velocity and diameter of propeller as the main design variables, and the ship advance, tactical diameter, transfer, 10°/10° first overshoot angle and 20°/20° first overshoot angle as output variables. We use the standard model-based calibration toolbox from commercial software Matlab to choose the 20 training data-set with Latin Hypercube Design, which are listed in Table 1.

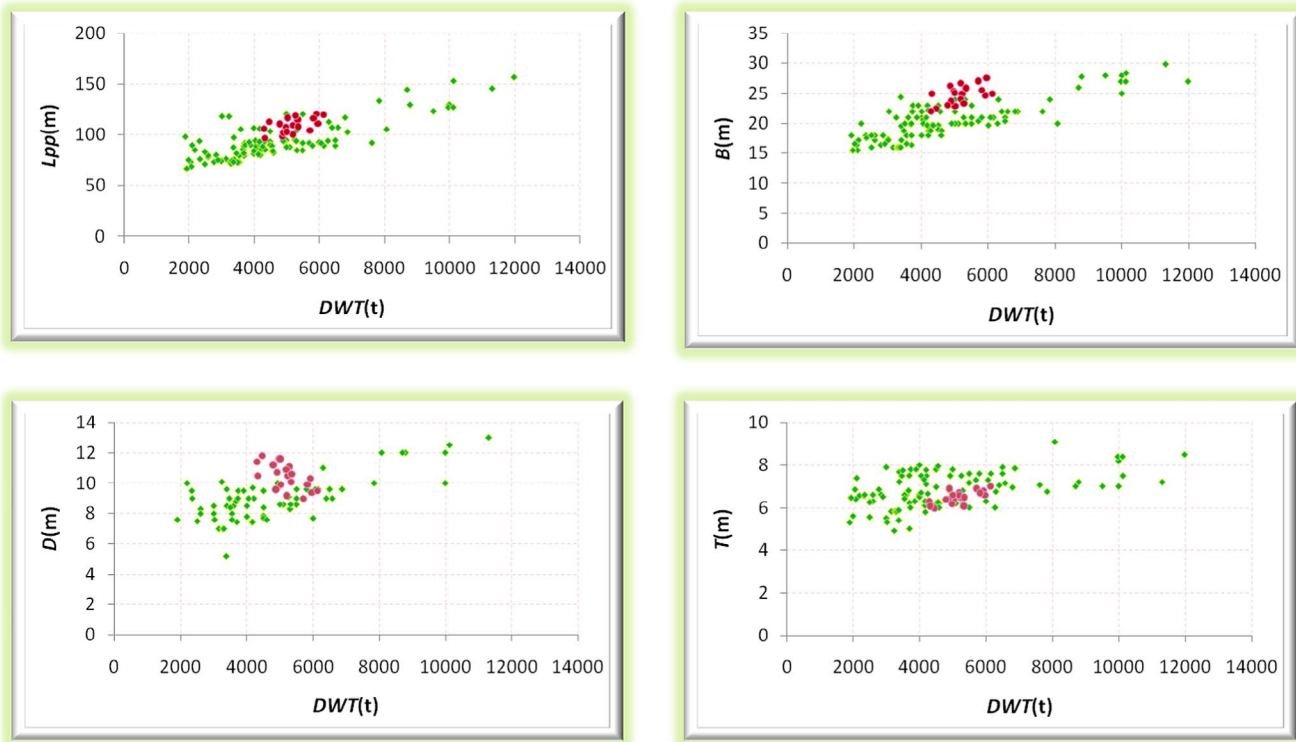


Figure 1. Distribution of vessels' principal characteristics.

Table 1. The design variables of 20 training ship data.

Ship type	Length L_{pp}/m	Breadth B/m	Depth D/m	Draught T/m	Velocity $V_j/Knot$	Propeller diameter D_p/m	Longitudinal centre of buoyancy L_{cb}/m
1	117.7	22.8	10.3	6.7	14.5	3.5	57.79
2	113.0	22.4	11.8	6.0	14.5	3.4	57.25
3	98.4	26.3	9.6	6.4	14.5	3.2	55.48
4	102.1	23.7	10.7	6.9	14.5	3.5	48.31
5	107.5	25.4	11.6	6.2	14.5	3.7	50.13
6	105.7	22.0	11.4	6.3	14.5	3.3	52.78
7	120.3	24.6	10.3	6.8	14.5	3.4	51.90
8	109.4	25.0	10.5	6.5	14.5	3.7	59.06
9	96.6	25.0	10.5	6.1	14.5	3.5	53.71
10	111.2	27.6	9.4	6.6	14.5	3.3	47.43
11	109.4	24.1	9.2	6.7	14.5	3.6	54.60
12	114.8	25.9	10.1	6.1	14.5	3.6	53.49
13	118.5	23.3	11.1	6.5	14.5	3.3	56.36
14	103.9	27.1	9.0	6.9	14.5	3.5	58.18
15	100.2	26.7	10.9	6.6	14.5	3.7	51.01
16	115.9	25.5	9.9	6.7	14.5	3.6	56.90
17	119.5	24.9	9.5	7	14.5	3.7	58.67
18	110.7	23	11.2	6.4	14.5	3.4	54.35
19	102.8	25.1	11.6	6.6	14.5	3.5	50.47
20	108	25.9	10.6	6.5	14.5	3.5	53.03

Before establishing the metamodels of seakeeping performance in multidisciplinary ship design optimization, we should first decide the calculation method for the ship manoeuvring performance of offshore support vessel. As the objective of this article is to develop a practical approximation model of ship manoeuvring performance in the hydrodynamic-based MDO at the early design stage, a practical calculation tool, based on the MMG (Ship Manoeuvring Mathematical Model Group) Model called Manoeuvring Manager from the commercial software NAPA, is used to compute the manoeuvring criteria. The ship

hull of one training ship is shown in Figure 2; the simulation of turning circle manoeuvre is shown in Figure 3; and the simulations of Zigzag test are shown in Figure 4.

The criteria described in IMO Resolution A.751 (18) (1993) [15] are commonly used to judge the manoeuvring characteristics of a vessel. Here the advance, tactical diameter, transfer, $10^\circ/10^\circ$ first overshoot angle and $20^\circ/20^\circ$ first overshoot angle are chosen as manoeuvring criteria to evaluate the performance for the offshore support vessel. These calculated manoeuvring criteria of 20 ship types are listed in Table 2.

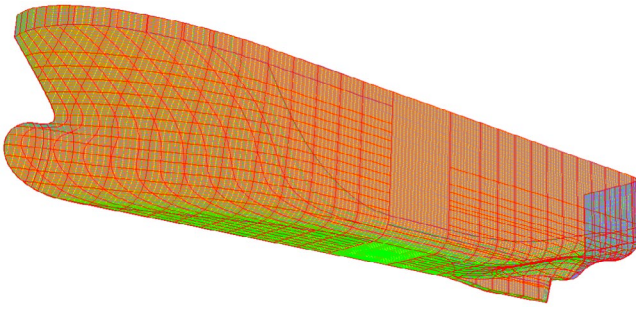


Figure 2. 3D layout of ship hull.

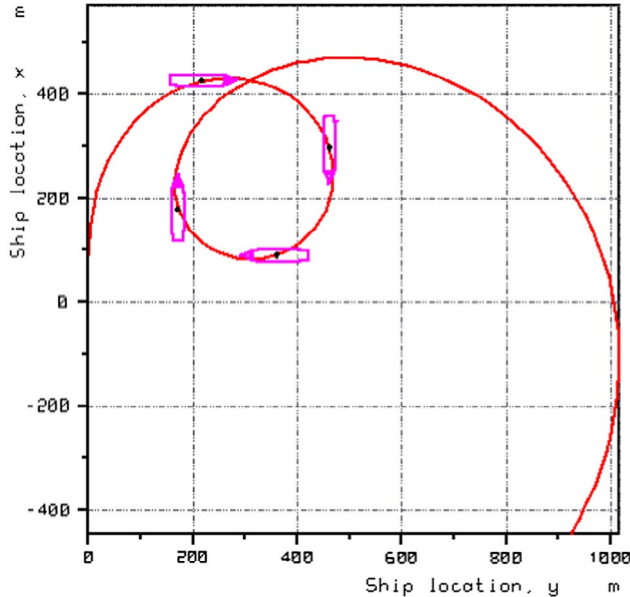


Figure 3. The simulation of turning circle manoeuvre.

Using these calculated values of manoeuvring criteria, the benchmarking methodology presented in this article can be used to establish metamodels of manoeuvring performance of offshore support vessels in the multidisciplinary ship design optimization without running expensive model tests or time-consuming

CFD calculations. Here, the programmes are written in Matlab and the metamodels of ship manoeuvring performance are constructed with the proposed ν -SPL-SVR. We separate two cases to demonstrate the efficiency of the new proposed support vector regression algorithm.

Case 1: At first, ship types 1 – 10 were selected as training data-sets and ship types 11 – 20 as test data-sets. The calculation results were compared with Manoeuvring Manager, ANN, classic SVR and SPL-SVR which are shown in Figure 5. Here, the calculation result for advance is listed in Table 3 for instance. The relative error (RE) and mean relative error (MRE) are applied as performance indices: $RE = \frac{y_i - y_i^*}{y_i}$, $MRE = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i - y_i^*}{y_i} \right|$ where y_i is the real value and y_i^* is the predicted value.

Case 2: Then similarly, ship types 11 – 20 were selected as training data-sets and ship types 1 – 10 as test data-sets. The results are shown in Figure 6. As an example of calculated data, the result for 10°/10° first overshoot angle is listed in Table 4.

The MRE comparison for the five manoeuvring criteria in two cases is listed in Table 5. From the results, we can see that the maximum MRE for ν -SPL-SVR in Case 1 is 3.34% and the minimum MRE is 3.08%; the maximum MRE for ν -SPL-SVR in Case 2 is 3.63% and the minimum MRE is 2.83%. Obviously, if the training ship data-sets, the kernel parameters and the calculation method for manoeuvring are chosen properly, we can use these metamodels to calculate the ship manoeuvring performance instead of CFD simulations and model tests in the preliminary ship design stage and also can obtain high fitting precision calculation result of manoeuvring performance in the time-consuming multidisciplinary ship design optimization.

5. Conclusions

The assessment of ship manoeuvring performance is studied in this paper including advance, tactical diameter, transfer, 10°/10° first overshoot angle and 20°/20° first overshoot angle. The metamodels for manoeuvring performance, which are established by the new ν -SPL-SVR algorithm in conjunction with LHS, are employed in place of expensive simulation and analysis codes and these metamodels can be used to evaluate the ship manoeuvring performance efficiently at preliminary design stages of offshore support vessel. Without using

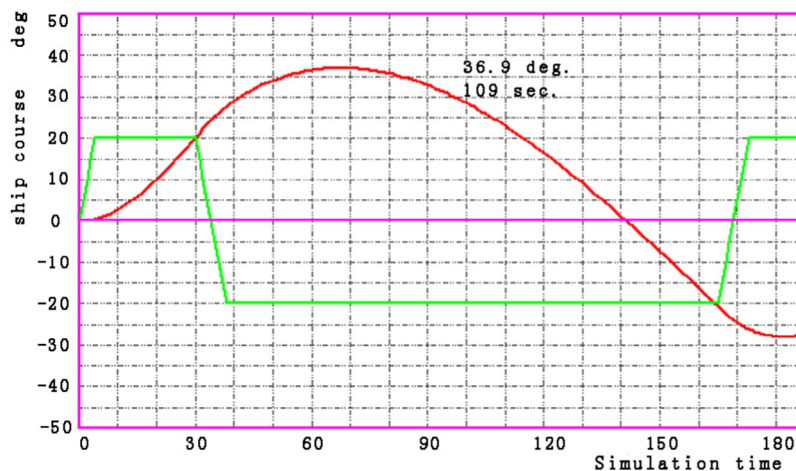
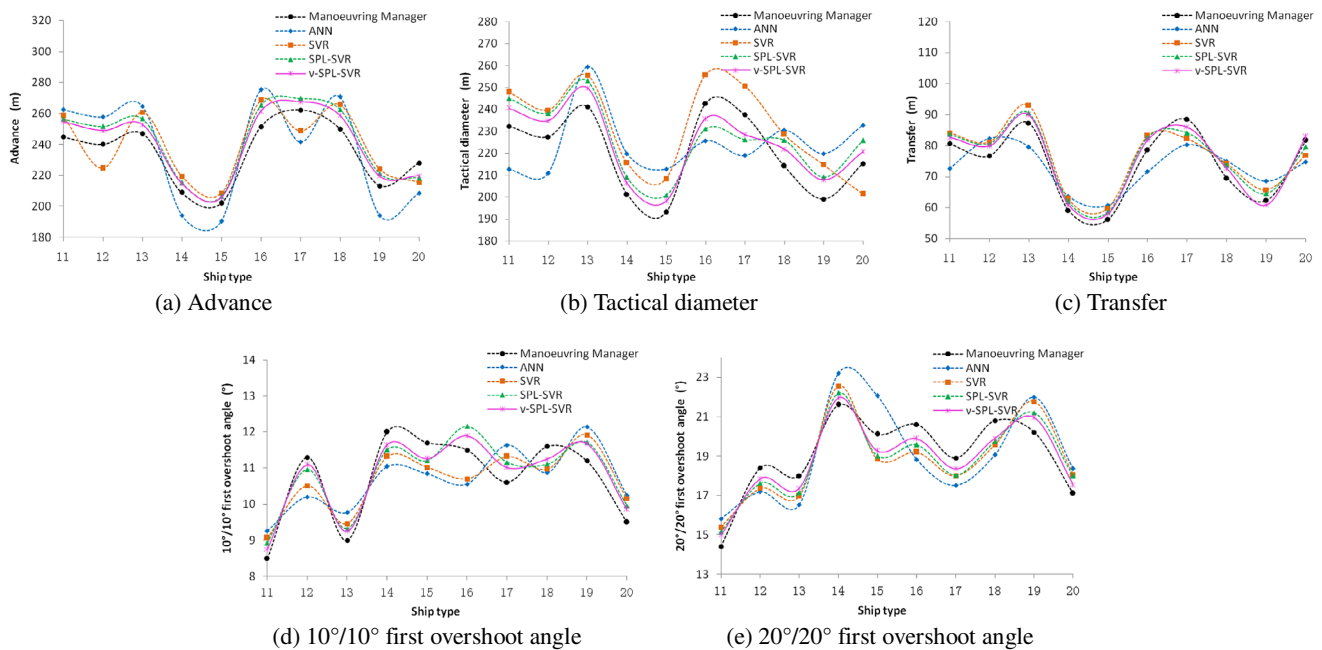


Figure 4. The simulation of Zigzag test 10°/10°.

Table 2. Calculated manoeuvring criteria of 15 training ship data.

Ship type (Unit)	Advance (m)	Tactical diameter (m)	Transfer (m)	10°/10° first overshoot angle (°)	20°/20° first overshoot angle (°)
1	259.8	232.6	81.9	9.7	22.3
2	235.8	246.6	96.2	10.2	19.9
3	197.7	188.3	53.9	11.5	21.1
4	205.3	196.6	63.6	11.4	20.9
5	219.6	209.2	65.6	12.0	20.5
6	215.8	207.5	70.9	9.5	17.6
7	237.5	231.8	77.1	10.7	17.4
8	223.9	214.4	69.8	11.2	19.6
9	195.4	183.5	54.9	11.4	21.0
10	229.6	219.0	69.6	11.3	22.5
11	244.8	232.3	80.6	8.5	14.4
12	240.1	227.4	76.7	11.3	18.4
13	247.1	241.2	87.3	9.0	18.0
14	208.8	201.3	59.1	12.0	21.6
15	202.0	193.0	56.2	11.7	20.1
16	251.3	242.7	78.7	11.5	20.6
17	262.2	237.5	88.5	10.6	18.9
18	250.0	214.1	69.5	11.6	20.8
19	213.3	199.0	62.3	11.2	20.2
20	228.0	215.3	81.6	9.5	17.1

**Figure 5.** The result of Case 1 for ship type 11–20.**Table 3.** Calculation result with relative error (RE) for advance.

Ship type number	Manoeuvring manager	ANN		SVR		SPL-SVR		v-SPL-SVR	
	(m)	Value (m)	Relative error (%)	Value (m)	Relative error (%)	Value (m)	Relative error (%)	Value (m)	Relative error (%)
10	244.8	262.3	7.14	258.3	5.53	256.2	4.66	254.6	3.99
11	240.1	257.6	7.28	224.6	−6.44	251.5	4.75	248.8	3.62
12	247.1	264.6	7.07	260.6	5.48	256.5	3.81	252.9	2.34
13	208.8	194.3	−6.96	219.3	5.05	215.2	3.07	214.8	2.87
14	202.0	190.5	−5.71	208.5	3.24	206.4	2.18	205.8	1.87
15	251.3	275.3	9.54	268.3	6.78	265.2	5.53	261.5	4.04
16	262.2	241.6	−7.87	248.6	−5.17	269.5	2.79	267.5	2.02
17	250.0	270.6	8.23	265.6	6.25	262.5	5.00	258.8	3.52
18	213.3	194.3	−8.92	224.3	5.17	221.2	3.71	219.5	2.93
19	228.0	208.5	−8.57	215.5	−5.47	218.4	−4.21	219.7	−3.62
20	244.8	262.3	7.14	258.3	5.53	256.2	4.66	254.6	3.99

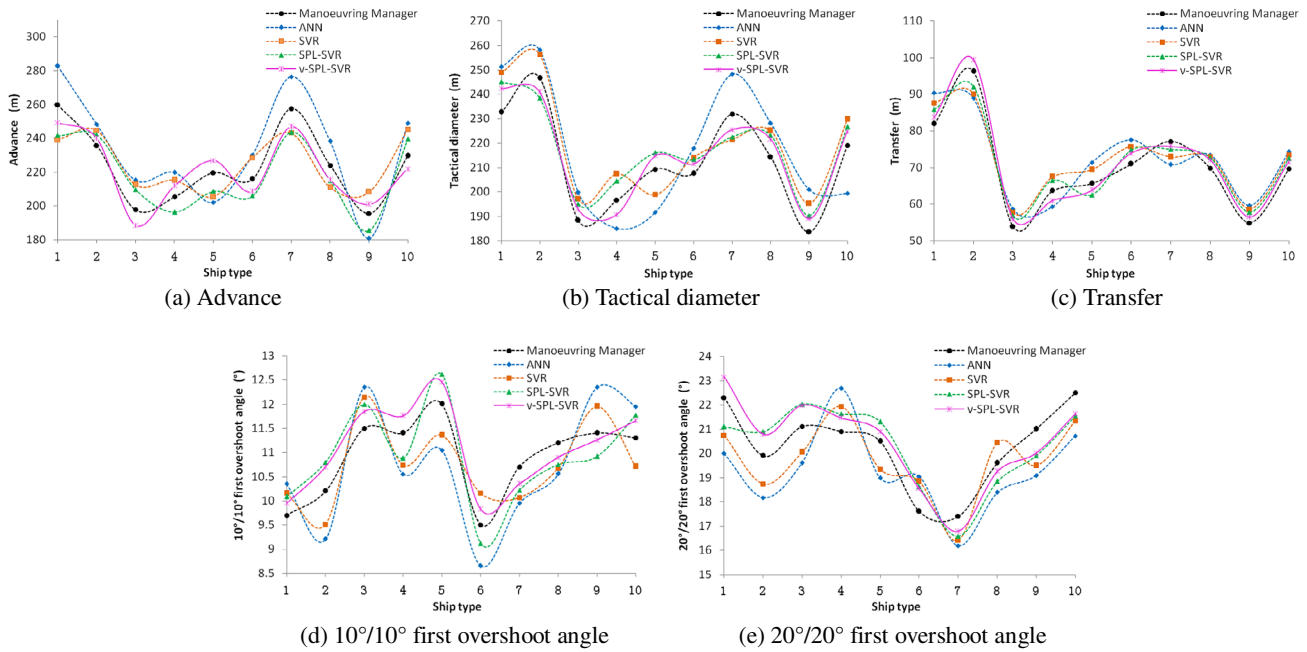


Figure 6. The result of Case 2 for ship type 1–10.

Table 4. Calculation result with relative error (RE) for 10°/10° first overshoot angle.

Ship type number	Manoeuvring manager	ANN		SVR		SPL-SVR		v-SPL-SVR	
	(m)	Value (m)	Relative error (%)	Value (m)	Relative error (%)	Value (m)	Relative error (%)	Value (m)	Relative error (%)
1	9.7	10.3	6.69	10.2	4.69	10.1	3.97	9.9	2.56
2	10.2	9.2	-9.75	9.5	-6.71	10.8	5.86	10.7	4.95
3	11.5	12.3	7.38	12.1	5.64	12.0	4.28	11.8	3.01
4	11.4	10.5	-7.47	10.7	-5.83	10.9	-4.55	11.8	3.16
5	12	11.0	-7.93	11.4	-5.38	12.6	5.15	12.5	3.81
6	9.5	8.7	-8.94	10.2	6.91	9.1	-4.05	9.8	3.36
7	10.7	9.9	-7.02	10.1	-5.93	10.2	-4.53	10.3	-3.28
8	11.2	10.6	-5.74	10.7	-4.64	10.8	-4.01	10.9	-2.70
9	11.4	12.3	8.32	12.0	4.86	10.9	-4.25	11.3	-1.25
10	11.3	12.0	5.76	10.7	-5.25	11.8	4.18	11.7	3.17

Table 5. The MRE comparison for the five manoeuvring criteria (Unit:%).

Manoeuvring criteria	Case 1				Case 2			
	ANN	SVR	SPL-SVR	v-SPL-SVR	ANN	SVR	SPL-SVR	v-SPL-SVR
Advance	7.73	5.46	3.97	3.08	7.43	6.11	4.85	3.43
Tactical diameter	8.37	6.51	4.80	3.27	7.00	4.98	3.75	2.83
Transfer	8.63	6.01	4.31	3.10	8.02	6.15	4.53	3.11
10°/10° first overshoot angle	8.30	6.28	4.45	3.27	7.50	5.58	4.48	3.12
20°/20° first overshoot angle	8.21	5.97	4.73	3.34	8.05	5.79	4.61	3.63

computationally expensive methods such as CFD or model tests, the main advantage of this methodology is to provide detailed and realistic operational profiles of ship designs at the early stage of the design process.

As part of the future work, metamodels of ship resistance, seakeeping and manoeuvring can be combined in the framework

of MDO to improve its convergence efficiency. Multidisciplinary and multi-objective optimization design problems widely exist in the field of ship design, development of effective framework for multidisciplinary and multi-objective optimization problems with uncertainties will be also considered as a future research direction

List of symbols:

L_{pp}	Length between perpendiculars	C	Penalty parameter
B	Breadth moulded	ξ, ξ^*	The parameters of classical SVR
D	Depth moulded	$\phi(x_i) \cdot \phi(x)$	The inner product of high-dimensional space
T	Draught moulded	$K(x_i, x)$	The kernel function
DWT	The deadweight tonnage	$\{x_i, y_i\}$	The training data-set
w_i	The weight factor	ε	Tube parameter for insensitive loss function
σ^2	Gaussian kernel parameter	ν	The parameter of ε

Disclosure statement

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Zhiyong Jiang is a professor of ship and ocean engineering, Jiangsu University of Science and Technology (JUST). His current research interests include ship advanced manufacturing technology, digital and computer application, and integrated manufacturing and software systems.

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